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Four Decades of Progress in Monitoring and Modeling of Processes in the Soil-Plant-Atmosphere System: Applications and Challenges

Analysis of inter-storm period soil moisture dynamics

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Abstract

Soil moisture temporal dynamics is the result of the interaction between the stochastic climate forcing and the buffering effect operated by the soil volume, depending on its hydraulics properties. To address an analysis of the soil moisture temporal variability, a number of input and output processes to the representative soil volume have to be modeled. Overall, at the point scale, input process corresponds to the effective rainfall occurrences whereas the output process correspond to the losses function represented by the evapotranspiration, sub-surface and deep percolation fluxes. The number and relative complexity make troublesome both the processes schematization and the interpretation of soil moisture dynamics.
In this study, observed soil moisture data, recorded over a 3 years period, have been explored to assess and characterize the dominating processes at an experimental site, located in Southern Italy, Campania region, with reference to inter-storm periods, when the soil water balance is only driven by the losses fluxes. About thirty inter-storm events, including five or more days, have been selected and the soil moisture depletion process has been explored. Soil moisture depletion over the experimental site occurs following a negative exponential law. The rate of soil water content reduction appears to be different over the seasons, with the highest rate occurring during the spring season, perhaps reflecting the higher vegetation water consumption during this particular period of the year. Initial soil water content seems also to affect the inter-storm dynamic, being the rate of depletion lower for low initial soil moisture contents. Multilevel recorded data also allowed the investigation of the importance of soil depth, with a depletion process rate being much more smoother in the deeper soil layer.

Keywords: soil moisture dynamic; inter-storm period; evapotranspiration.

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1. Introduction

At the point scale, the soil moisture dynamic in the root zone can be described by a stochastic differential equation, taking the form of:

$$n \cdot z \cdot \frac{d\theta}{dt} = \varphi[\theta(t), t] - \chi[\theta(t)] \quad (1)$$

where n is the soil porosity, z the root zone depth, θ the soil water content, $\varphi[\theta(t),t]$ and $\chi[\theta(t)]$ respectively the rate of infiltration from rainfall and the rate of soil moisture losses from the considered soil layer [1-3]. The number and relative complexity of hydrological processes embedded in equation (1) make troublesome both the interpretation of soil moisture dynamics and the model calibration for predictive purposes. During inter-storm period, that is during a period of time between two successive rainfall events, the rainfall infiltration rate is absent, and the soil moisture variation over time is only driven by the rate of losses, mainly corresponding to the evaporative E and leakage K processes. Soil water content dynamic is greatly simplified in these cases, and it can be analytically demonstrate that the soil drying correspond to an exponential process [4].

But probabilistic stochastic modeling does not represent the only possibility to mathematically approach the soil moisture dynamic. A number of experimental studies have also been oriented on the use of statistical space and time series analysis, where the soil properties and along with these the unsaturated soil water content transport, given the soil profile heterogeneity cannot be considered as random function but as structured processes, that can be modeled with reference to classical ARMA and ARIMA models [5-6].

In the case of stream discharge, Vogel and Kroll [7] demonstrated that treating the watershed as a linear reservoir, where the relation between the stream discharge and the source volume is an exponential relation, make possible to consider that the stream discharge itself is an autoregressive process. Following this simplification, in the following, an empirical analysis of experimental data has been performed confirming the existence of a negative exponential recession of the soil moisture profile over the time. The rate of the recession is related to climate and event scale variability and such relations are then applied to reproduce, at the investigated plot, the soil moisture dynamic during inter-storm periods.

2. Experimental data analysis

The experimental plot, a $450 m^2$ (15×30 m) filed equipped with a meteorological station and six FDR multi-level soil moisture measurements probes, is located in Southern Italy, within the University of Salerno's campus. Further details about preliminary analyses can be found in [8-10].

A number of about 30 inter-storm events, occurring from October 2004 to December 2007 have been selected. For each event, lasting at least five days, soil moisture data observed at 10 minutes time scale, have been aggregated on a daily time scale, and have been plotted against the time. Multilevel recorded data, at 10 and 30 cm depth allowed the investigation of the importance of soil depth on the depletion process rate.

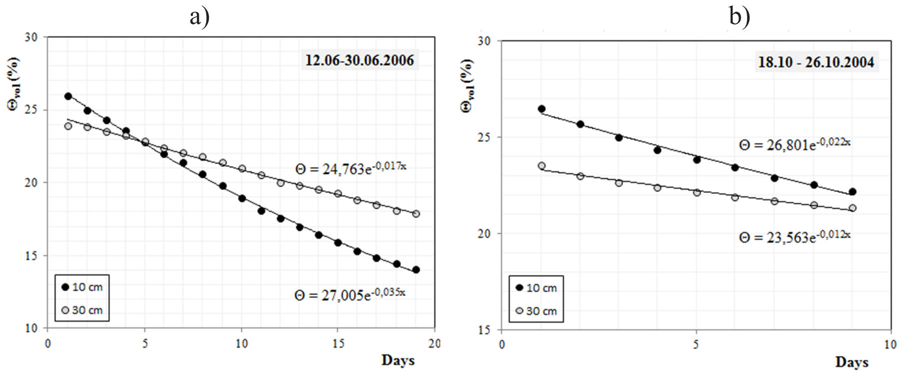

Fig. 1. Observed inter-storm soil moisture dynamic, at 10 and 30 cm, for (a) dry season; (b) wet season.

Fig. 1 illustrates, as an example, the temporal dynamic for both a dry and wet seasons inter-storm events. As showed in the same picture, inter-storm events can be empirically described by an extremely simple negative exponential relation:

$$\theta(t) = \theta_0 \exp(-\alpha \cdot t) \qquad\qquad \theta_0 = \theta(t = 0) \qquad (2)$$

similarly to the formulations used for the description of the streamflow hydrograph recession limb [11]. On a qualitative base, Fig. 1 also indicates that the rate of the depletion process is smoother in the deeper layer, as it would have been expected on a conceptual base, because of the greater inertia against the evapotranspiration process, compared to the surface soil layers, which is perhaps the major source of losses during non-rainy period, especially in the dry summer season. Parameters θ_0 and α set respectively the initial condition and the rate of the depletion process and their estimation also gives a quantitative assessment of soil drying velocity. In particular the parameter α is characterized by variation both at the seasonal and at the event scale, behind a variability along the soil profile.

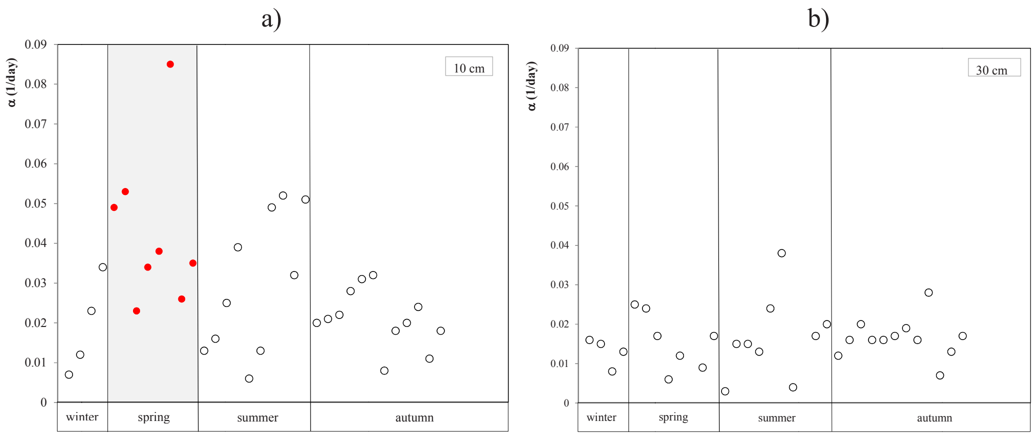

Fig. 2. Parameter α seasonal scale variability, at (a) 10 cm; (b) 30 cm.

The seasonal scale variability is depicted in the following Fig. 2 where, for the two analyzed soil layer depths, α estimates are illustrated, highlighting the seasons time windows. The most evident difference, at this point quantitatively assessed, is the smaller range of variability showed by α at the deeper layer and its consistency throughout the seasons windows. On the contrary, surface layers show a large variability in the depletion process velocity, with great differences between the seasons and with the largest values occurring during the spring season, perhaps reflecting the higher vegetation water consumption during this particular period of the year. Discrepancies between soil layers and seasons are summarized in Table 1, where the average α estimates are given.

The event scale variability is quantified in the following Fig. 3 where, for each soil layer depth and for each event, α estimates have been plotted against θ_0 the observed soil moisture content at the inter-storm period starting point. The relation between α and θ_0 appear quite clear for the surface layer. The velocity of the depletion process is faster for large soil water content availability.

Table 1. Average seasonal α parameter (1/day).

Season	10 cm	30 cm
Winter	0.019	0.013
Spring	0.043	0.017
Summer	0.030	0.016
Autumn	0.021	0.016

This behavior holds until a threshold value for θ_0 of about 24%, whereas ones the θ_0 initial condition exceed the threshold there is no longer a dependence of α estimates on the initial conditions. θ values larger than 24% generally occur during the winter season and during the early autumn season: perhaps in case of very large soil water content availability the differences in α estimates depend on differences in the climate conditions of that particular event, with a particular reference, as an example, to the air temperature. This explanation would also justify the relation between α and θ_0 for the deeper layer. In this case, it is still possible to identify a threshold value for θ_0, which seems to correspond to the one identified for the surface layer, but the relation between α and θ_0 when the threshold is exceeded, has a lower scatter extent.

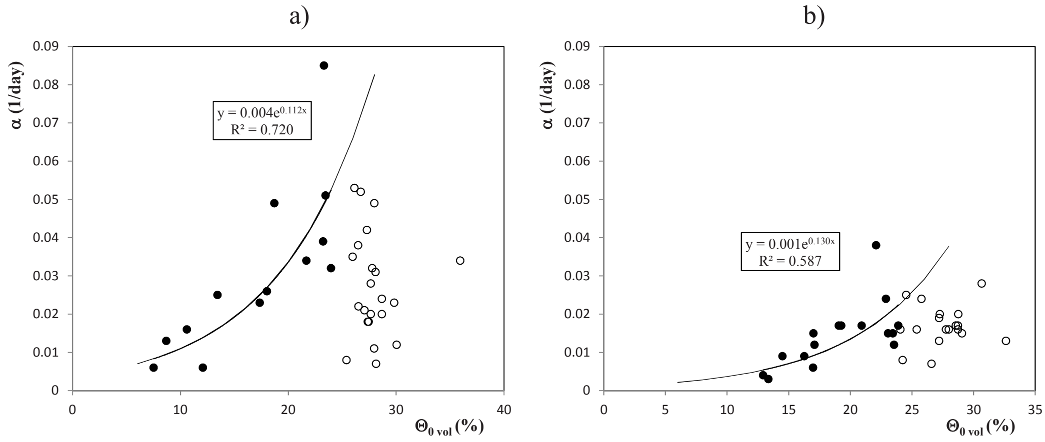

Fig. 3. Parameter α event scale variability, at (a) 10 cm; (b) 30 cm.

3. Empirical inter-storm dynamic modelling

Qualitative and quantitative assessment about the inter-storm period dynamic previously discussed, can also represent a useful modeling tool when soil moisture dynamic, between two subsequent rain events, is aimed to be simulated through the use of an empirical framework, having however a conceptual base. During inter-storm period, soil water content variability is driven by the losses phenomena, mainly represented by the evapotranspiration and the deep drainage processes. With reference to the evapotranspiration process, two main controls act on it: on one side the soil water content abstraction atmosphere power, which is a climate control, on the other side the moisture content availability, which is a soil water balance control. This premise correspond to the parameter α explorative assessment analysis: the seasonal scale variability would in fact relate to a climate dependent variability, depending above all on the air temperature conditions, whereas the event scale variability would in fact relate to the soil water content availability dependence.

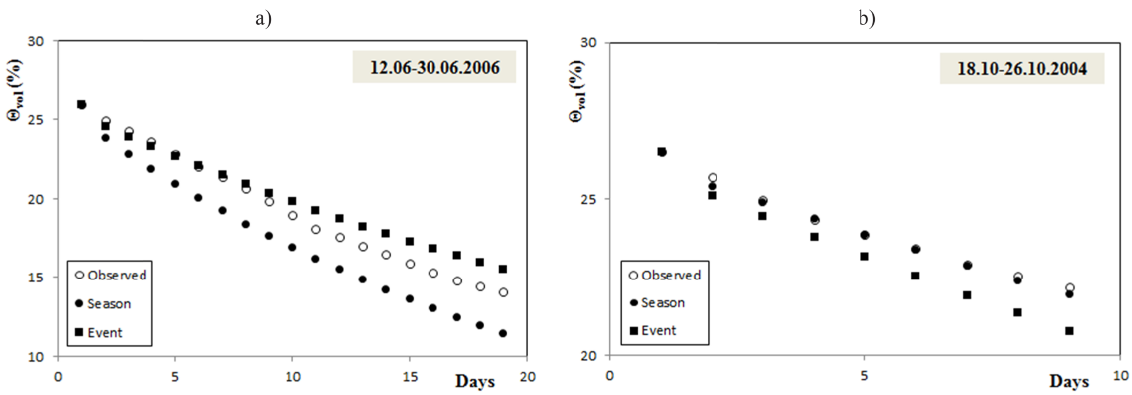

Fig. 4. Observed and empirically modeled inter-storm soil moisture dynamic, at 10 cm, for (a) dry season; (b) wet season.

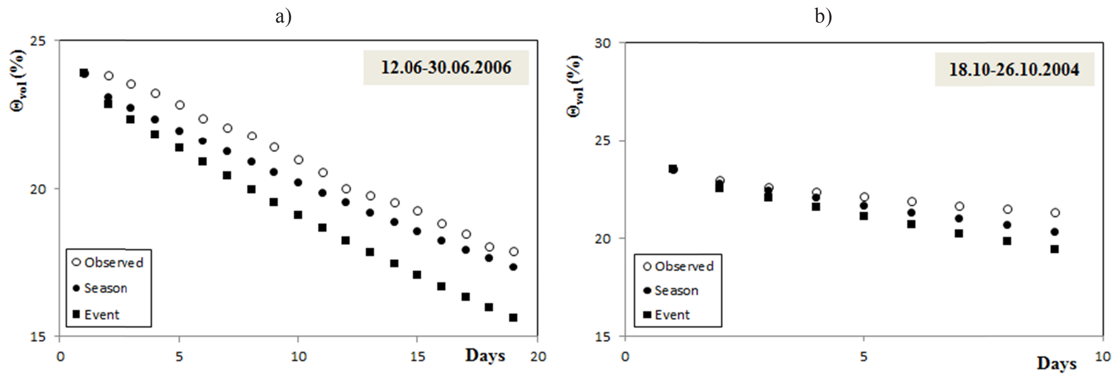

Fig. 5. Observed and empirically modeled inter-storm soil moisture dynamic, at 30 cm, for (a) dry season; (b) wet season.

Equation (2) have been used to empirically model soil water content depletion curves, for the same analyzed inter-storm period. Initial conditions, that is the θ_0 value have been considered as the observed ones, whereas an a-priori value for the α parameter has been set for each event, according to the seasonal

(α_{season}) and event scale (α_{event}) variability, as quantified in Figs. 2 and 3. The α_{season} parameter has been set for each event, at for each soil layer depths, according to the value indicated in Table 1, as a function of the season event occurrence. The α_{event} parameter has been set for each event, at for each soil layer depths, according to the following rule. More in detail, if the initial soil water content was less than the threshold value detected in Fig. 3, than the exponential relations:

$$\alpha_{event} = 0.004 \cdot \exp(0.112 \cdot \theta_0) \qquad 10 \text{ cm} \tag{3}$$

$$\alpha_{event} = 0.001 \cdot \exp(0.130 \cdot \theta_0) \qquad 30 \text{ cm} \tag{4}$$

provided α_{event} estimates. If instead the initial soil water content was greater than the threshold value, than an average value has been set to α_{event} = 0.027 for the surface layer and α_{event} = 0.017 for the deep layer. Modeled and observed depletion curves have been compared and, as an example, the following Figs. 4 and 5 illustrate the performances for a dry and a wet season events, respectively for the surface and the deep layer.

The empirical model goodness-of-fit has been further tested through the calculation of NSE and the ratio error. The Nash-Sutcliffe index represent a measure of the modeled process variance which is not explained from the observed variable and it is calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (\theta_{obs,i} - \theta_{mod,i})^2}{\sum_{i=1}^{n} (\theta_{obs,i} - \overline{\theta}_{obs})^2} \tag{5}$$

The ratio error (σ) represents instead a measure of an absolute modeling error:

$$\sigma(\%) = \frac{\theta_{obs} - \theta_{mod}}{\theta_{obs}} .100 \tag{6}$$

The results are summarized in the following Tables 2 and 3.

Table 2. Empirical modeling goodness-of-fit indicators (10 cm).

Period	Season	NSE_{season}	NSE_{event}	σ_{season}	σ_{event}
18.10-26.10.2004	Autumn	0,99	0,61	0,4	3,28
28.10-05.11.2004	Autumn	0,48	0,86	5,27	2,42
13.03-24.03.2005	Winter	-0,48	0,4	15,64	9,67
01.04-08.04.2005	Spring	0,94	0,64	1,81	5,66
27.04-05.05.2005	Spring	0,96	0,49	2,36	9,14
07.05-12.05.2005	Spring	0,53	0,94	4,18	1,1
20.05-24.05.2005	Spring	-0.60	-0,27	7,21	3,3
19.06-30.06.2005	Spring	0,59	0,97	6,65	1,60

01.07-10.07.2005	Summer	-0,27	0,87	5,75	1,83
14.07-02.08.2005	Summer	-2,5	0,96	16,4	1,58
09.08-20.08.2005	Summer	-5,63	0,94	11,51	1,03
25.08-29.08.2005	Summer	0,76	0,62	3,11	3,96
10.10-18.10.2005	Autumn	0,84	0,98	2,54	0,83
23.10-31.10.2005	Autumn	0,97	0,46	0,66	3,41
09.11-13.11.2005	Autumn	0,74	-0,36	1,23	2,89
20.12-24.12.2005	Autumn	-6,6	-14,75	3,69	5,29
04.01-11.01.2006	Winter	0,04	-3,74	2,12	5,47
01.05-06.05.2006	Spring	0,63	0,88	8,05	4,52
13.05-31.05.2006	Spring	0,79	0,82	8,28	7,99
12.06-30.06.2006	Spring	0,7	0,93	10,87	4,87
02.07-06.07.2006	Summer	-0,21	0,94	3,52	0,69
14.07-23.07.2006	Summer	0,9	0,28	1,23	5,46
22.08-26.08.2006	Summer	0,88	0,94	2,03	1,5
31.08-11.09.2006	Summer	0,22	0,98	16,6	2,49
28.09-03.10.2006	Summer	0,88	0,97	1,71	0,76
08.10-19.10.2006	Autumn	0,82	-1,82	3,96	18,22
24.10-30.10.2006	Autumn	0,88	0,14	1,31	3,59
13.11-19.11.2006	Autumn	0,89	0,11	0,89	2,89
23.11-27.11.2006	Autumn	0,99	0,66	0,28	1,67
29.11-03.12.2006	Autumn	-11,36	-24,14	3,7	3,54
23.12-28.12.2006	Autumn	0,35	-1,32	1,89	3,54
27.01-31.01.2007	Winter	-9,25	-27,37	3,08	5,22
17.04-24.04.2007	Spring	1,0	0,53	0,55	4,98
05.05-09.05.2007	Spring	-11,78	-0,18	5,58	1,73
29.08-03.09.2007	Summer	-83,68	-1,96	7,92	1,46

Table 3. Empirical modeling goodness-of-fit indicators (30 cm).

Period	Season	NSE_{season}	NSE_{event}	Ratio error (season)	Ratio error (event)
18.10-26.10.2004	Autumn	0,35	-1,68	2,13	4,46
28.10-05.11.2004	Autumn	0,96	0,95	0,66	0,68
13.03-24.03.2005	Winter	-1,33	-5,38	3,64	6,04
01.04-08.04.2005	Spring	0,77	0,2	1,42	2,78
27.04-05.05.2005	Spring	0,88	0,89	1,92	1,89
20.05-24.05.2005	Spring	0,62	0,97	1,3	0,3
19.06-30.06.2005	Spring	-1,96	0,97	5,14	0,49
01.07-10.07.2005	Summer	-5,35	0,93	4,45	0,44
14.07-02.08.2005	Summer	-100	-7,03	8,55	2,53
25.08-29.08.2005	Summer	0,91	0,82	0,78	1,15
10.10-18.10.2005	Autumn	0,89	0,92	1,65	1,35
23.10-31.10.2005	Autumn	0,97	0,97	0,68	0,62
09.11-13.11.2005	Autumn	0,99	0,97	0,22	0,35
20.12-24.12.2005	Autumn	-0,02	-0,24	1,62	1,79
04.01-11.01.2006	Winter	0,2	0,93	1,37	0,78
01.05-06.05.2006	Spring	-20,5	-2,32	4,08	1,62

13.05-31.05.2006	Spring	-0,2	0,93	7,27	1,59
12.06-30.06.2006	Spring	0,87	0,17	3,19	8,36
02.07-06.07.2006	Summer	0,37	0,89	1,49	0,52
14.07-23.07.2006	Summer	0,76	-0,31	1,85	3,29
22.08-26.08.2006	Summer	0,46	0,61	3,05	2,59
31.08-11.09.2006	Summer	0,89	0,9	1,57	1,23
28.09-03.10.2006	Summer	0,97	1,0	0,5	0,16
08.10-19.10.2006	Autumn	0,75	0,68	2,44	2,82
24.10-30.10.2006	Autumn	0,98	0,95	0,4	0,57
13.11-19.11.2006	Autumn	0,96	0,96	0,53	0,53
23.11-27.11.2006	Autumn	0,46	0,59	2,75	2,4
29.11-03.12.2006	Autumn	-7,75	-8,79	2,78	2,94
23.12-28.12.2006	Autumn	0,81	0,74	0,94	1,12
27.01-31.01.2007	Winter	0,99	0,6	0,15	1,12
17.04-24.04.2007	Spring	0,9	0,9	1,16	1,19
05.05-09.05.2007	Spring	0,1	-0,33	1,49	1,83
29.08-03.09.2007	Summer	-61,8	-2,03	4,32	0,98

4. Conclusions

The paper has presented an empirical analysis aimed at understanding the soil moisture dynamic during inter-storm period for a particular experimental plot, located in Southern Italy. At first, a number of about 30 inter-storm events have been selected and the soil moisture variation over time has been approximated through an exponential negative law. The exponential relation is described by two parameters: an initial condition in terms of θ_0 and the rate of the process itself, named α. The empirical analysis showed that the rate of the process is affected by a climate scale and an event scale variability. On a seasonal scale, the soil drying process appeared faster during the spring season, perhaps reflecting the higher vegetation water consumption during this particular period of the year. At the event scale, the dependence of α on the initial condition θ_0 indicated that the rate of the depletion process also depends on soil water availability. During inter-storm period, soil water content variability is highly driven by the evapotranspiration losses, controlled by a climate and a soil water balance controls. This would correspond to the parameter α assessment and gives a conceptual base to the empirical modeling based on the findings of the experimental explorative analysis. The empirical negative exponential law can be indeed used for modeling purposes once optimal values for α have been estimated: as a tendency inter-storm events occurring during the dry season appeared to be better modeled when reference to the event scale variability is made, whereas inter-storm events occurring during rainy periods appeared to be better modeled when reference to the seasonal scale variability is made. Indeed, in dry seasons evapotranspiration losses are driven by soil water availability whereas in rainy seasons evapotranspiration losses are controlled by climatic factors.

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